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A Review of Fabric Defect Detection Techniques

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ABSTRACT
In modern manufacturing industries quality inspection is an important aspect. For a long time, fabric defect inspection process is carried out by human visual inspection hence it is insufficient and costly. Therefore, automatic fabric defect inspection is required to reduce the cost and time waste caused by defects. The development of fully automated web inspection system requires robust and efficient fabric defect detection algorithms. Various techniques have been developed to detect fabric defects. Categorization of fabric defect detection techniques is useful in evaluating the qualities of identified features. Therefore on the basis of nature of features from the fabric surfaces, the proposed approaches have been characterized into three categories; statistical, spectral and model-based.
Keywords:- Quality Assurance, Industrial Inspection, Fabric Defect Detection, Automated Visual Inspection.

I. INTRODUCTION

Textile Fabric [1] materials are used to prepare different categories and types of Fabric products in the textile industry. In the textile industry, fabric faults or defects are responsible for nearly 85% of the defects [2]. Manufactures recover only 45-65% of their profit from second or off quality goods [3]. It is very important to detect, to identify and to prevent these defects from reoccurring. There are many kinds of fabric defects. Much of them are caused by machine malfunctions and have the orientation along pick direction, they tend to be long and narrow. Other defects are caused by faulty yarns or machine spoils. An automated defect detection and identification system enhances the product quality and results in improved productivity to meet both customer needs and to reduce the costs associated with off-quality.

Inspection is the process of determining whether a product has deviated from a given set of specifications. Fabric defect detection [4] can be defined as the process of determining the location and/or extend of a collection of pixels in a fabric image with remarkable deviation in their intensity values or spatial arrangement with respect to the background texture.

In the textile industry, inspection [5], is done to assure the fabric's quality before any shipments are sent to customers, because defects in fabrics can reduce the price of a product by 45% to 65%.Currently, the quality assurance of web processing is mainly carried out by manual inspection. However, the reliability of manual inspection is limited by ensuing fatigue and inattentiveness. Indeed, only about 70% of defects can be detected by the most highly trained inspectors.

Textile industries are facing increasing pressure to be more efficient and competitive by reducing costs. Therefore automated detection of defects in textile fabrics [5], which results in high-quality products and high-speed production, is definitely needed. Automated fabric defect detection can usually result in lower labor costs, improved quality, faster inspection and increased reliability [4].

II. RELATED WORK

Texture is one of the most important characteristics in identifying defects or flaws. The task of detecting defects has been largely viewed as a texture analysis problem. In this paper the proposed defect detection techniques have been classified in three categories: statistical, spectral and model-based.

In spectral approaches texture is characterized by texture primitives or texture elements, and the spatial arrangement of these primitives [6]. Thus, the primary goals of these approaches are firstly to extract texture primitives, and secondly to model or generalize the spatial placement rules. The random textured images cannot be described in terms of primitives and displacement rules. Therefore, spectral approaches are not suitable for the detection of defects in random texture materials. In spectral- domain approaches, the texture features are generally derived from the Fourier transform [7,8], Gabor transform [9,10] and Wavelet transform [11].

The Fourier transform (FT) has the desirable properties of noise immunity and enhancement of periodic features. The author Tsai D. And Heish C. [12] used the Fourier transform to reconstruct textile images for the defect detection. The line patterns in the textile images, supposed to be defects, are taken out by removing high energy frequency components in the Fourier domain using a one dimensional Hough transforms. The difference between the restored image and the original image were considered as potential defects.

Kumar A. and Pang G. [13] perform fabric defect detection using only real Gabor functions. They used a class of self similar Gabor functions to classify fabric defects. They also investigated defect detection using only imaginary Gabor functions as an edge detector. Bodnarova A. Bennamoun M. and Latham S. [14] applied a Fisher cost function to select a subset of Gabor functions based on the mean and standard deviation of the template feature images to perform textile flaw detection.

Sari-Sarraf H. and Goddard J.S. [15] have developed a fabric defect detection system that can detect small defects with an overall detection rate of 89%. Their defect detection scheme uses the low-pass and the high-pass 'Daubechies' D2 filter. Kumar A. and Gupta S.[16] have used mean and variance of "Haar" wavelet coefficient for the identification of surface defects. The fabric texture can also be considered as noise and removed using wavelet shrinkage.

Model - based texture analysis methods are based on the construction of an image model that can be used not only to describe texture, but also to synthesize it. Cohen F., Fan Z., and Attali S. [17] used Gaussian Markov Random Fields (GRMF) to model defect free textile web. The inspection process was treated as a hypothesis testing problem on the statistics derived from the GMRF model. The images of fabric to be inspected are divided into small windows in inspection process; a likelihood ratio test is then used to classify the windows as non– defective or defective. The testing image was partitioned into non-overlapping sub-blocks where each window was then classified as defective or non-defective.

In Statistical texture analysis methods measure the spatial distribution of pixel values. Statistical methods can be classified into first- order, second order and higher- order statistics based on a number of pixels defining the local features. The first –order statistics estimate properties like the average and variance of individual pixel values, second and higher order statistics on the other hand estimate properties of two or more pixel values occurring at specific locations relative to each other. The defect detection method uses many texture features such as co-occurrence matrix, morphological operations, fractal dimensions, and etc.

Fractal-based texture analysis was introduced by Pentland. Voss refers to box counting as the process of estimating the probability that m points lie in the box. Keller J., Crownover R. and Chen S. [18] proposed a modification of method due to Voss, which presents satisfactory results up to FD = 2.75. The utilization of fractal dimension is investigated by Conci A. and Proenca C. B [19] for discriminating defective areas. The decision for defect declaration is based on the variation of FD. This method is computationally enough to be suitable for PC implementation, but presents very limited experimental results which suggest 96% detection on eight types of defects. The localization accuracy of these defected defects is very poor.

Zhang Y. F and Breese R. R [20] have detailed on morphological operations for detection of fabric defects. The practical utility of this approach is limited as most of the commonly occurring fabric defects will be missing from the binary image generated from the simple thresholding operation. Detecting defects morphologically on spatially filtered images of fabrics produces better results [21], particularly when the fabric is fine and contains defect of small size. In this experiment the morphological operations are only performed on periodic images, unlike the case in where the entire structure of threshold fabric image was utilized.

The co-occurrence matrix is one of the most popular texture analysis tools for the fabric defect detection. It is also known as spatial gray-level dependence. The principle is based on repeated occurrences of different gray level configurations in a texture. The co-occurrence matrix contains information about the position of pixels having similar gray level values [22]. Texture features such as energy, entropy, contrast, homogeneity, and correlation, are then derived from the co-occurrence matrix. Harlick R. M., Chanmugam K. and Dinstein I[23] derived 14 features from the co-occurrence matrix and used them successfully for characterization of textures. Other researchers proposed the gray level co-occurrence matrix approach as a base to develop an automated fabric inspection system. Tsai I., Lin C., and Lin J. [24] have detailed fabric defect detection while using only two features, and achieved a classification rate as high as 96%. Rosler R. N. U [25] has also developed a real fabric defect detection system, using co-occurrence matrix features, which can maintain 95% of the defects as small as $1mm^2$ in size.

III. CONCLUSION

The brief review of fabric defect detection methodologies using image processing techniques gives us possible development of this application area. These available techniques are classified into three categories: statistical, spectral and model-based. The core ideas of these methodologies are discussed along with their advantages and disadvantages whenever known. The statistical, spectral and model – based approaches gives different results and hence the combination of the approaches can give better results, than either one individual approach and is suggested for future research. There is also a need of some standard datasets in order to carry out fair comparative analysis.

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